Semarak Engineering Journal

Journal homepage:
https://semarakilmu.my/index.php/sej/index
ISSN: 3036-0145

Hand Pose Recognition for Activities of daily living tasks using wearable stretchable sensor for Telerehabilitation

Hafizu Ibrahim Hassan[1], Norsinnira Zainul Azlan[2,*], Anis Nurashikin Nordin[3], Mohd Azri Abd Mutalib[4]

[1] Department of Mechatronics Engineering, Faculty of Engineering, Ahmadu Bello University, Zaria 810211 Kaduna State, Nigeria
[2] Department of Mechatronics Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia
[3] Department of Electrical and Computer Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia
[4] Machine Design Section, Machinery Technology Centre, SIRIM Berhad, Lot 1A, Persiaran Zurah, Kawasan Perindustrian Rasa, 44200 Rasa, Selangor, Malaysia

ARTICLE INFO

Article history:
Received 12 August 2025
Received in revised form 12 January 2026
Accepted 8 March 2026
Available online 3 April 2026

Keywords:
Stretchable Sensor; Hand Pose Recognition; Machine Learning; ADL tasks; Telerehabilitation

ABSTRACT

The recognition of hand poses during activities of daily living (ADLs) in post-stroke patients using wearable technologies offers greater precision and detail compared to conventional clinical assessments. This study aims to deploy wearable stretchable sensors to evaluate the accuracy of detecting hand poses for six different ADLs using machine learning (ML) algorithms. The selected tasks are derived from the Motor Activity Log (MAL), a clinical assessment tool used by therapists to quantify post-stroke recovery. An initial study involving 20 healthy subjects is conducted to determine the best sensor configuration for capturing distinct hand poses. Four sensor placement configurations are considered: thumb, index finger, middle finger, and wrist (TIMW); thumb, index finger, middle finger, and back of the hand (TIMB); thumb, index finger, wrist, and back of the hand (TIWB); and all fingers (thumb, index, middle, and ring fingers). The t-Distributed Stochastic Neighbour Embedding (t-SNE) technique is utilized to visualize clustering patterns, with the TIMW configuration demonstrating the most distinct separation of ADL tasks. Data from the four sensors are acquired and processed offline. Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Random Forest (RF) classifiers are implemented to recognize the six ADLs, achieving accuracies of 97.22%, 95.83%, and 46.15%, respectively. Compared to previous researches utilizing IMUs and flex sensors, the proposed stretchable sensor system demonstrates a promising performance. Future work will extend this study to post-stroke survivors to further validate the system's effectiveness in rehabilitation settings.

1. Introduction

Stroke remains a major global health concern, ranking among the leading causes of disability and mortality, with 13.7 million new cases reported annually [1]. A significant proportion of stroke survivors experience permanent disabilities, including motor, cognitive, and language impairments,

* *Corresponding author.*
E-mail address: sinnira@iium.edu.my

https://doi.org/10.37934/sej.13.1.168189

as well as psychological challenges, increasing the demand for rehabilitation services. The primary goal of rehabilitation is to monitor and evaluate the patient's movement quality and paretic limb usage during activities of daily living (ADL). In recent years, tele-rehabilitation has emerged as an effective alternative for delivering rehabilitation services, reducing patient limitations while enhancing accessibility. This approach enables remote physiotherapy support, ultimately improving patients' quality of life [2]. By promoting frequent therapeutic exercises, tele-rehabilitation facilitates faster recovery while easing the workload on physiotherapists, allowing a single professional to manage multiple patients simultaneously [3][4]. However, for tele-rehabilitation to be effective, accurate recognition of hand poses during ADL tasks is essential for monitoring patient progress remotely. Occupational therapists (OTs) play a crucial role in stroke rehabilitation, assisting individuals in regaining their ability to perform meaningful activities. Through clinical assessment techniques, they evaluate patients' capabilities using tools such as the Motor Activity Log (MAL), Action Research Arm Test (ARAT), and Barthel Index (BI) [5][6]. However, these assessments are often subjective, as different therapists may interpret a patient’s condition differently. Integrating wearable sensors into the evaluation process can enhance objectivity, providing precise measurements to support clinical assessments [7].

Hand pose recognition is a technique used to detect and interpret various hand gestures, with applications in sign language recognition, human-robot interaction, and Human Activity Recognition (HAR)[8][9]. Within the scope of ADL task recognition, hand pose recognition is essential for ensuring effective tele-rehabilitation. Researchers have explored two primary methods for recognizing hand gestures and human activities: computer vision-based approaches and wearable sensor-based techniques [10]. Wearable sensors have significantly advanced HAR research, with studies such as those by Halim *et al*. [8] and Sarka *et al*. [11] utilizing inertial measurement unit (IMU) datasets like WISDM, UCI-HAR, PAMAP2, and MHEALTH. While these methods have shown success in HAR applications, certain ADL tasks, such as turning a doorknob, opening a water tap, and unlocking a padlock, remain underexplored. These tasks are crucial for assessing stroke recovery, necessitating precise sensor placement on the fingers or hand to capture movement deformations accurately [12]. Stretchable sensors, made from flexible materials that alter their electrical properties in response to strain, offer a promising solution. These sensors provide a comfortable, lightweight, and highly sensitive alternative for motion measurement. Stretchable sensors typically operate based on resistance or capacitance changes, depending on its deformation. They come in various forms, including tape, mesh, and cord, offering flexibility and unobtrusiveness while ensuring accurate hand motion tracking for rehabilitation purposes [13].

Various works exploited machine learning and deep learning methods for hand pose recognition while performing human daily activity using a set of computer vision sensors and wearable sensors. Computer vision, as its name suggests, focuses on utilizing images and computer graphics for analyzing and accomplishing hand pose recognition [14]. Numerous studies have utilized various vision-based sensors, including Red Green Blue (RGB) cameras, RGB-D cameras like the Kinect sensor, Leap motion control sensors, and Infrared (IR) sensors, to capture images for hand pose recognition [15]. Wadhawan *et al*. [16] and Kwolek *et al*. [17] utilized an RGB camera to recognize hand gestures used in sign language. They employed Convolutional Neural Networks (CNNs) for the recognition of Japanese and Indian sign languages, achieving accuracies of 92.1% and 99.72%, respectively. Additionally, Li *et al*. [18] and Dennis *et al*. [19] proposed RGB cameras for hand pose recognition. They employed a Hierarchical Decision Classifier and CNNs for sign language recognition, achieving an accuracy of 97% using the CNN classifier. Rastgoo *et al*. [20] combined RGB and Leap motion control sensors to recognize hand gestures in American Sign Language (ASL) and achieved an accuracy of 99.59% using CNNs. Bakheet *et al*. [21] utilized an RGB-D camera for hand gesture recognition, employing the Support Vector Machine (SVM) machine learning algorithm and achieving an accuracy of 93.3%. However, despite the advanced capabilities of high-specification cameras, which are present in most smartphones, several challenges persist, including limited field of view, high computational costs, and the necessity for multiple cameras to overcome issues related to depth perception and occlusion.

On the other hand, the wearable sensors are garnering substantial interest due to their potential to provide continuous, real-time physiological information via dynamic, noninvasive measurements of the parameter [22]. Wearable sensors are becoming increasingly common in many different applications, including fall detection, health monitoring, sleep tracking, sports, fitness tracking, and more [23]. A. Van Gastel *et al*. [24] investigated the bend sensor, stretchable sensor and IMU sensor to evaluate the hand movement. IMU sensors achieved the highest accuracy compared to the other two sensors. However, IMU sensor dataset leads to high computation cost in assessing and monitoring the recovery level of stroke patients remotely. M. A. al Rumon *et al*. [25] designed a stretchable sensor from textile material for health monitoring. The developed stretchable sensor has been used to monitor the heartbeat of subject when conducting six tasks and achieved R-square value of 0.8791. S. Jiang *et al*. [26] designed a stretchable e-skin patch sensor which has been used to classify 9 ASL and achieved classification accuracy of 94.4%. Charmayne *et al*. [27] placed an IMU sensor on the wrist to measure hand movement when conducting three ADL tasks. A statistical analysis of the continuous time series data has been carried out to ascertain whether the two systems' resulting velocities have been similar during the task. An average coefficient correlation of 0.947 has been achieved for the three tasks considered. Chen *et al*. [28] placed five IMU sensors on the wrists, forearms, and abdomen to collect the accelerometer and gyroscope data when conducting 19 ADL/IADL tasks. Four machine learning algorithms have been compared for the classification of the 19 tasks and achieved classification accuracy of 56%, 79%, 97%, and 97% for DT, RF, SVM, and XGBoost respectively. Shakerian *et al.* [29] deployed an IMU sensor on microcontroller for real-time human activity recognition using CNN for the activity's prediction. Six activities, which were stationery, jumping, walking, jogging, sitting, and crouching were considered and a total of 90.4% accuracy was achieved. Sarka *et al*. [11] deployed the IMU datasets of UCI-HAR, WISDM, MHEALTH, PAMAPS, and HHAR to evaluate the performance of the proposed feature selection method. K-NN algorithm has been deployed to classify the activities and achieved accuracy of 99.45%, 99.38%, 99.90%, 98.29%, and 97.72% for the dataset respectively. Ramli *et al*. [30] developed a wearable stretchable sensor for facial expression detection. Three sensors have been placed on the forehead, top of the mouth and the chin to recognize four facial expressions which include neutral, happy, sad, and disgusting expressions. Distinct patterns have been observed for the four facial expressions considered. Masum *et al*. [13] deployed a commercial stretchable sensor in classifying facial expression. The sensors have been placed on the forehead, top of the lip, and the chin to classify neutral, happy, sad, and disgusting facial expression. A classification accuracy of 95% has been achieved using a random forest machine learning algorithm.

The IMU sensor is widely utilised for ADL recognition. However, recognizing hand-related ADLs, such as opening a doorknob or turning a water tap, remains challenging since the IMU sensor is typically mounted on the wrist, limiting its ability to capture fine hand movements. Flex sensors offer a promising alternative, as they can be placed directly on the fingers to improve recognition accuracy. However, their limited range restricts their effectiveness in capturing complex hand motions. Consequently, this study focuses on exploring the conformability and flexible nature of stretchable sensors for the recognition of hand-related ADLs using different machine learning algorithms. The research extensively investigates the best hand positions for placing stretchable sensors during the selected ADL activities, explores three machine learning algorithms to improve the accuracy of hand pose recognition, and evaluates the computational time of the three models for subsequent real-time application. The findings of this study will assist therapists in objectively classifying the recovery levels of post-stroke patients. The rest of this paper is organized as follows. Section 2 will describe the methodology, the results are presented and discussed in Section 3 and finally conclusion is drawn in Section 4.

2. Methodology

2.1 Experimental Protocol and Data Acquisition

Ten healthy subjects have been recruited for the study. At this stage, only the data from healthy patients are used to study the feasibility of the machine learning based on stretchable sensors data in recognizing the user's hand pose in performing the 6 ADL. The participants have been selected in random with different race (i.e. Asians and Africans) and gender. The study has obtained an ethical approval from International Islamic university Malaysia Research Ethics Committee (IREC) with an approval number of IREC 2023-079. Table 1 details the general demographic characteristics of the participants. Majority of the participants are males (85%) and females (15%). The average age of the participants was 31 ±7 years old. About 90% of the participants use their right hand for ADL and 10% their left hand for ADL activities. The participants agreed and signed the consent form to take part in the experiment.

The stretchable sensor type SS-C kit from Elastisense Sensor Technology Company Aabenraa, Denmark (LEAP Technology Company) as illustrated in Figure 1, has been used for the data collection. Table 2 details the specification and the settings for the stretchable sensor. The data is acquired at a sampling frequency of 500Hz, by placing the stretchable wearable sensors on three fingers and wrist of the subject's hand. With a measurement range of 0.1 to 5nF and a resolution of 1pF, the stretchable sensor ensures accurate data collection and runs on a 5V power source. It weighs 85g and operates between 10°C and 60°C, making it lightweight for wearable applications. The sensor offers flexible connectivity by Bluetooth and a USB cord. With its four sensor channels module, multi-point data collection is possible for precise hand movement identification.

Table 1
Demographic characteristic of the participants.

Characteristics	Mean / Count
Age	31 ±7
Gender	85% Male/ 15% Female
Race	30% Africans/ 70% Asians
Education	Postgraduate/ Undergraduate
Handedness	90% Right hand/ 10% Left hand
BMI	24.8 ±4.2

Table 2
Stretchable sensor specification.

Specification	Value
Power Supply	5V
Measurement Range	0.1 – 5nF
Resolution	1pF
Operating Temperature	10 – 60̊ c
Weight	85g
Communication Platform	Bluetooth and USB cable
Number Sensor channels	4 Channels

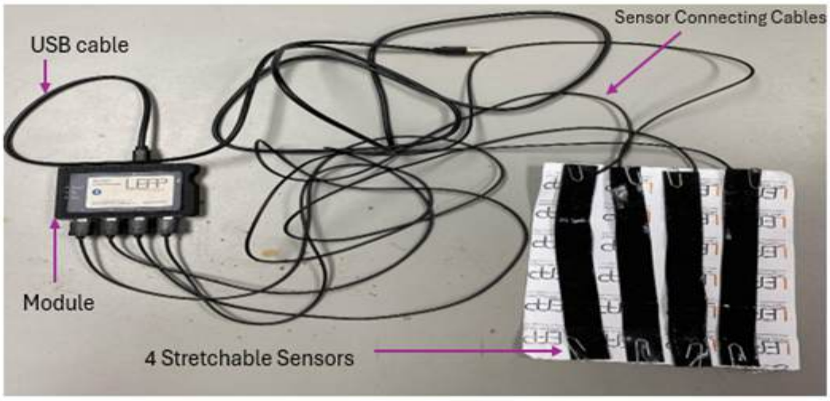


Fig. 1. Stretchable sensor kit from LEAP Technology

2.2 Sensor Placement Arrangement

The stretchable sensors have been placed at 4 positions on the hand to obtain the best arrangement with the best signals. The ideal configuration involves determining the placement of the four stretchable sensors to capture distinct hand pose patterns while performing the Activities of Daily Living (ADL) tasks. Four potential arrangements have been assessed to identify the best positioning which are:

i. thumb, index finger, middle finger, and wrist (TIMW)
ii. thumb, index finger, middle finger, and back of hand (TIMB)
iii. thumb, index finger, wrist, and back of hand (TIWB), and
iv. all finger (All Fingers).

The four sensor arrangements are shown in Figure 2. In this study, the manipulation board commonly utilized in Malaysian government hospitals has been employed as in Figure 3. It consists of 6 ADL tasks for hand rehabilitation, which are:

i. Turning the doorknob (Task 1),
ii. Turning the water tap (Task 2),
iii. Sliding the door latch (Task 3),
iv. Removing the plug head (Task4),
v. Turning the padlock key (Task 5), and
vi. Pressing the switch (Task6)

The 6 ADL tasks have been selected from the Motor Activity Log-45 (MAL-45) tasks used by occupational therapists for clinical assessment of patients.

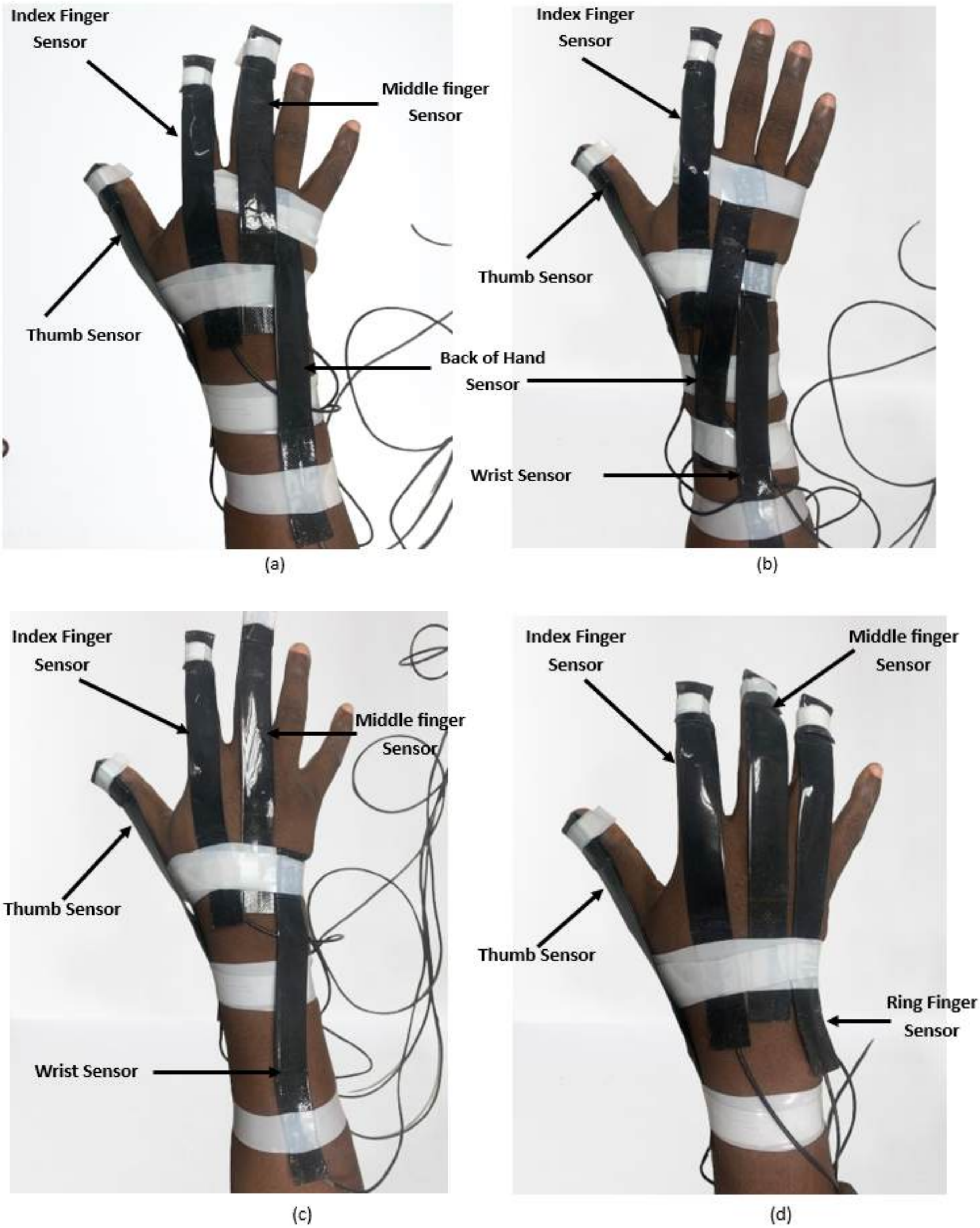


Fig. 2. Sensor Placements Arrangements (a) TIMB (b) TIWB (c) TIMW and (d) All-fingers

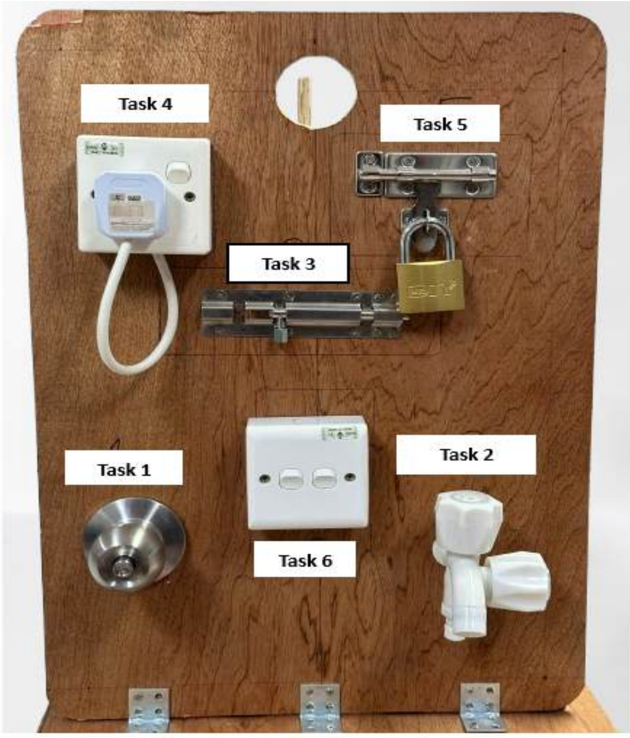


Fig. 3. Manipulation board for hand rehabilitation in Malaysian government hospitals

The experiment has been conducted according to the following procedures:

i. The manipulation board is placed on a 65cm height table and a chair without armrest is placed opposite to the manipulation board.
ii. The subject receives a brief explanation on the data collection procedure and conducts a trial session.
iii. The subject places his/ her dominant hand on the table where it is indicated start/stop.
iv. The subject performs Task 1 after been instructed to start and places his/ her hand back to the starting point, which indicates the completion of the first cycle of task1.
v. Each task is performed thrice with an interval 10secs for validation.
vi. After each task, the data are saved before the starting of the next task and the subject rests to avoid fatigue.
vii. The next task cycle commences when the subject is ready to continue.
viii. The procedure is repeated for Task 2, Task 3, Task 4, Task 5, and Task 6.
ix. The experiment ends after the subject completes the 6 ADL tasks on the manipulation board.

All rotational tasks (Tasks 1, 2, and 5) are standardized as clockwise rotations to ensure consistency in performing the ADL-based tasks. Participants have been instructed to turn the handle or key in a clockwise direction to maintain uniformity. Task 3 requires them to slide the latch lock linearly to open it, while Task 4 involves removing the plug head from the socket. In Task 6, participants have used their index and middle fingers to switch on the light, although with slight variations in individual technique. Figure 4 illustrate the experiment setup for the data collection. The set up encompasses the manipulation board for the 6 ADL tasks, the stretchable sensor, and the 4-channel interface system with the specification as specified in Table 2, computer mouse for setting the parameters of the sensor, the keyboard for saving the datasets, the monitor that displays the data, and the Dell CPU desktop with Intel core i7, 3.4GHz processor, 16GB RAM and 250GB storage capacity. Four stretchable sensors are connected to interface system and the interface system is connected to the CPU via USB cable. The 5V is supplied from the CPU via the USB powers of the interface system. Figure 5 represents the data acquisition setup for healthy subject. The four stretchable sensors are placed on the best locations of the hand and fixed to the location with a self-fusing, silicone electrical tape. The subjects have been educated on the posture of the hand for each of the task. The subject sits opposite to the manipulation board and places the dominate hand on the table where the start/stop is located. The data acquired from the experiment are stored and processed offline.

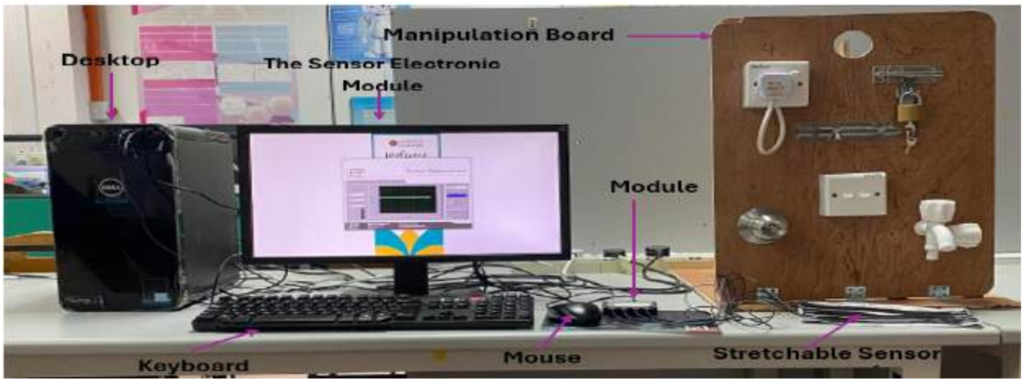


Fig. 4. Hardware experimental setup

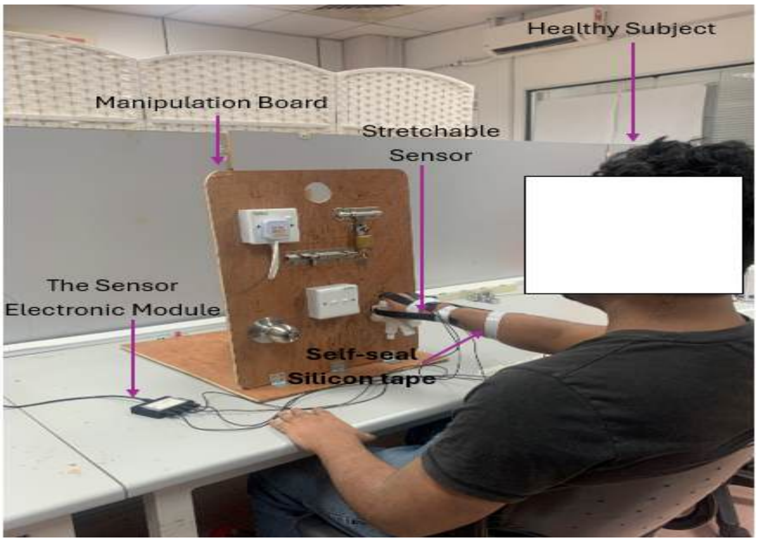


Fig. 5. Data acquisition setup.

2.3 Data Processing

The MATLAB program version 2023a is utilized to process the obtained data. Since the data have varying window lengths, the data are smoothen using MATLAB data cleaner software with a Gaussian Filter and a common smoothing factor of 0.25. Next, the smooth data are normalized using the equation-based min-max normalization method calculated as

$$Xnew = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

where *Xnew* is the normalize value, *X* is each of the data point, *Xmin* is the minimum value of the data, and *Xmax* is the maximum value of the data.

In this study, Root Mean Square (RMS) is used for feature extraction and the formula can be written as

$$Xrms = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \quad (2)$$

where $Xrms$ is the RMS value of the data, Xi is the i^{th} data value, and N is the numbers of data in the dataset.

2.3 Machine Learning Algorithm

Various ML algorithms have been proposed in the literature for hand pose recognition. However, the most popular methods are Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), Decision Tree (DT), XGBoost, and Random Forest (RF) classifiers. In this paper, the (SVM), K-NN, and RF ML algorithms have been deployed for classifying of the hand pose while performing the 6 ADL tasks.

SVM machine learning algorithm is a supervised learning primarily used for classification tasks, though it can also be applied to regression tasks. SVM works by finding the optimal hyperplane that best separates different classes in the feature space. This hyperplane is chosen to maximize the margin, which is the distance between the hyperplane and the nearest data point from each class known as support vector [28]. SVM algorithm handles both linear and non-linear classification problems with the latter handled by the kernel function. The accuracy of the classification depends on the maximum margin. The mathematical formula for the linear and non-linear classifications are

$$f(x) = w^T x + b \quad (3)$$

$$f(x) = \sum_{i=1}^{n} \alpha_i \, y_i \, K(x,\ x_i) \ + b \quad (4)$$

where $f(x)$ is the classification function for linear and non-linear classification, x is the dataset, w^T is the weight vector (coefficients) perpendicular to the hyperplane, b is bias term, α_i are the Lagrange multiplier, y_i is the class label of the i^{th} training sample, $K(x,\ x_i)$ is the kernel function that computes the inner product between two feature vectors x and x_i[31].

Support Vector Machine algorithm handles multi-class classification using various strategy and the most common deployed strategy are the one vs all and one-vs-one approach. In the one vs all strategy, the **k** numbers of binary classifiers (SVMs) are train to predict membership in one of the **k** classes. However, in one- vs- one approach, the classifier uses $\frac{\boldsymbol{k(k-1)}}{\boldsymbol{2}}$ SVMs to predict membership in one of the **k** classes. In this paper, the one to all approach has been utilized to classify the hand pose when performing the 6 ADL tasks.

K-NN algorithm is a supervised learning which is based on intuitive principle, where similar things exist near each other. This implies that K-NN algorithm predicts the classification of a data point based on the majority class among its nearest neighbors [32][33]. The classification relies on the distance metrics to identify closest neighbors to a query point. The Euclidean distance metric is commonly used though other metrics like Manhattan or Minkowski can also be used [34]. In this study, K value of 6 is considered for the K-NN training. The mathematical formula for the Euclidean metrics can be written as

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \quad (5)$$

where $d(p,q)$ is the Euclidean distance between points p and q, p_i and q_i are the i^{th} coordinates of points p_i and q_i respectively, n is the number of dimension or feature in the dataset [34].

Random forest (RF) is an ensemble learning algorithm, where multiple models of decision tree are combined to improve the overall performance and robustness of the system and used for both classification and regression tasks in machine learning. It operates by constructing multiple decision trees during training and outputs the class that is the mode of the classes for classification and mean prediction for regression of the individual trees. Each tree is trained independently on a random subset of the training data and feature [35]. Random forest employs a technique called bagging, where multiple decision trees are trained on random subsets of the training data with replacement. This helps in reducing variance and overfitting. In the classification tasks, Random Forest aggregates the prediction of individual tree by voting for the most popular class among all trees [13]. The entropy evaluates the accuracy of the classification as low entropy implies good classification with all the homogenous feature data in specified nodes and the opposite implies poor classification of the training dataset. The equation for Entropy is given as

$$H(x) = -\sum_{i=1}^{n} p(x_i).\,log_2\big(p(x_i)\big) \quad (6)$$

where $H(x)$ is the entropy of the dataset x , $p(x_i)$ is the probability of occurrence of x_i in the dataset, and n is the total number of classes [13].

The pre-processed stretchable sensor dataset for healthy individuals is prepared and structured for training in machine learning. Three machine learning models have been implemented to recognize the hand pose while performing the six Activities of Daily Living (ADL) tasks, which are SVM, K-NN, and RF. The training dataset is composed of 480×100001 elements, with the class labels located in the final column. The dataset is split into 70% for training purposes and 30% for model testing. Evaluation of the models' performance for the machine learning algorithms is based on several metrics, including confusion matrices, accuracy, precision, recall, F1-score, and the duration of training/testing. Accuracy measures the fraction of instances the model correctly predicts out of the total instances evaluated. A True Positive (TP) occur when the model correctly predicts a positive case, while a True Negative (TN) is obtained when it correctly predicts a negative case. Conversely, a False Positive (FP) occurs when the model incorrectly predicts a positive case, and a False Negative (FN) occurs when it incorrectly predicts a negative case. Accuracy can be calculated using these four outcomes as [11][36]

$$Accuracy = \frac{Tp+TN}{Tp+TN+FP+FN} \quad (7)$$

where Tp is the True Positive, TN is the True Negative, FP is the False Positive, and FN is False Negative

Based on the total number of samples identified as positive, precision is defined as the proportion of accurately identified positive samples. Precision is governed by [11][36][36].

$$Precision = \frac{Tp}{Tp+FP} \quad (8)$$

where Tp is the True Positive, and FP is the False Positive.

The percentage of correctly identified positive samples among all positive trials is known as recall and it can be computed as [11]

$$Recall = \frac{Tp}{Tp+FN} \quad (9)$$

where Tp is the True Positive, and FN is False Negative.

The F1-score is harmonic mean of precision and recall, is a thorough estimate of the model's correctness and it can be calculated as

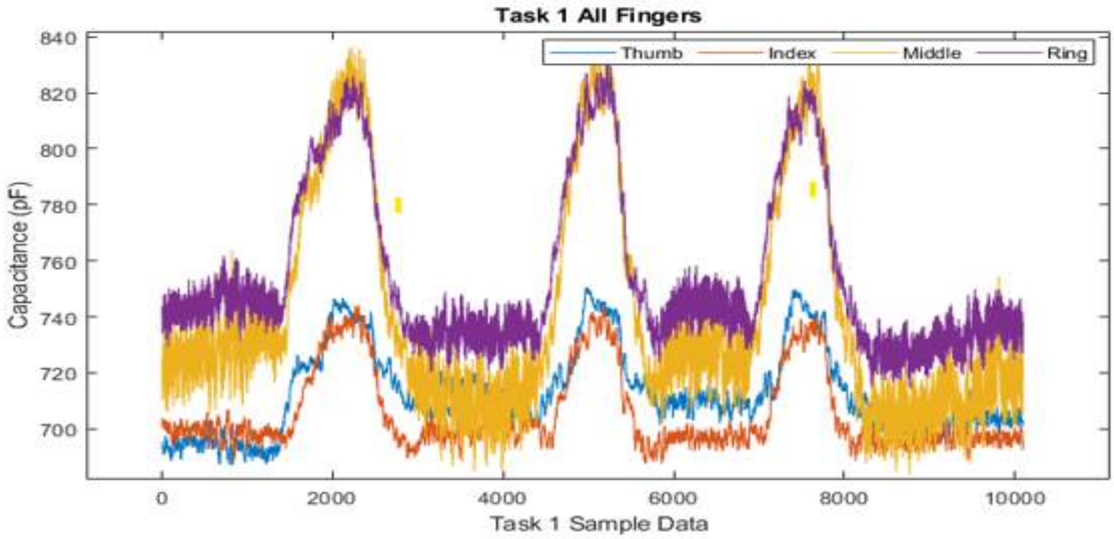
$$F1\_score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (10)$$

The overall classification model's performance is represented by the confusion matrix, which is a square matrix. The class label instances that are true are represented by rows in the confusion matrix, while the class label instances that are predicted are represented by columns. The diagonal components of this matrix tally with the number of trials in which the true and anticipated labels coincide. The confusion matrix is a crucial statistic tool for evaluating the performance of the develop model [11].

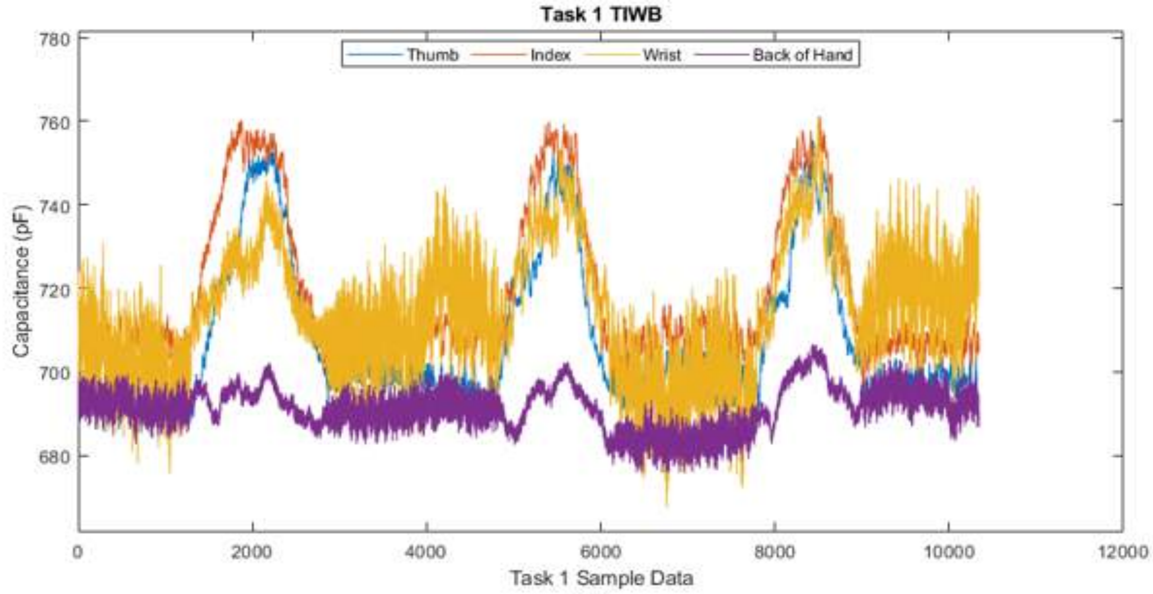
3. Results

3.1 Sensors Placement Arrangement.

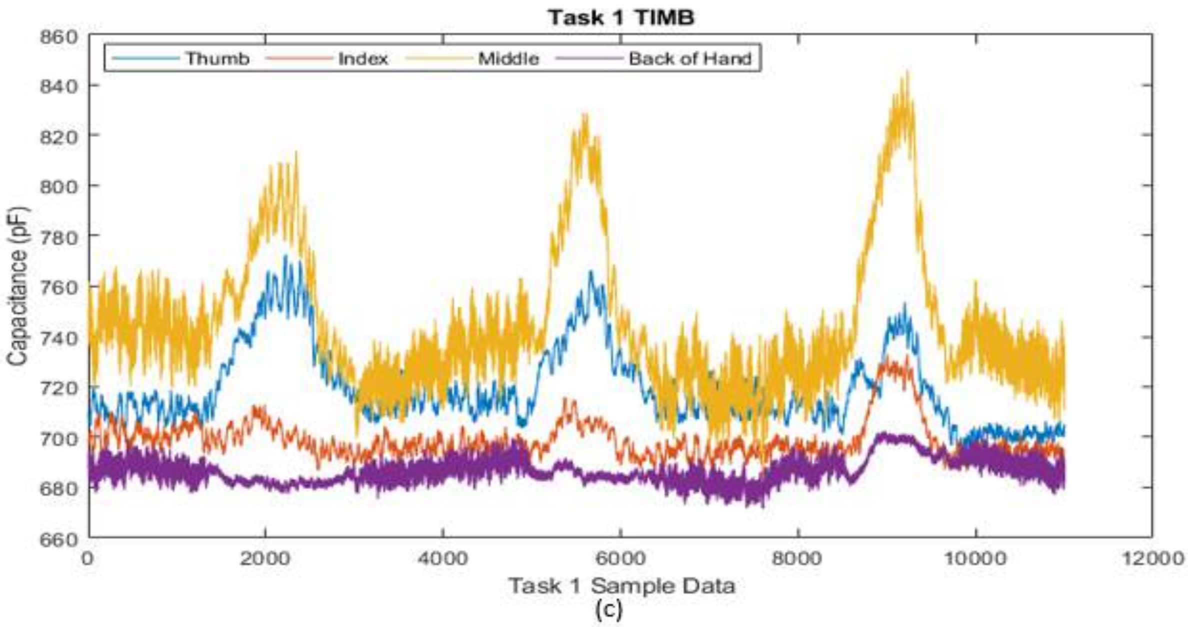
Figure 6 presents the raw data plots for Task 1 across the four sensor placement arrangements. The four sensor arrangements yield varied patterns, with TIMB and TIMW displaying similar patterns. However, TIMB exhibits considerable noise, potentially impacting classification accuracy. The all-fingers arrangement demonstrates consistent patterns across the six ADL tasks, even though with differences in capacitance magnitude based on task. Yet, this arrangement fails to exhibit distinct patterns for individual tasks. TIWB reveals distinct patterns for all six tasks, but proximity between the back of the hand and wrist sensors introduces noise, affecting the signal clarity. In contrast, TIMW arrangement exhibits minimal noise and distinct patterns, effectively distinguishing between tasks. The plots reveal that all three trials exhibit a similar pattern, though with noise during both active and resting periods. However, the TIMW arrangement demonstrated less noise, and a more distinct pattern compared to the other configurations. A t-distributed Stochastic Neighbour Embedding (t-SNE) test is conducted to visualize the clustering of each arrangement based on the six ADL tasks. The aim of the test is to observe the clustering pattern among the ADL tasks. The t-SNE is implemented on PyCharm (scikit-learn) with learning rate chosen as the hyperparameter on the 10 healthy subjects' data. The TIMW sensors arrangement demonstrate well-separated cluster for 4 out 6 ADL tasks, indicating a strong distinction between these activities. However, the All-fingers, TIWB, and TIMB sensor arrangements showed significant overlap, suggesting poor task differentiation as illustrated in Figure 7.


Task 1 All Fingers
Thumb
Index
Middle
Ring
Capacitance (pF)
Task 1 Sample Data

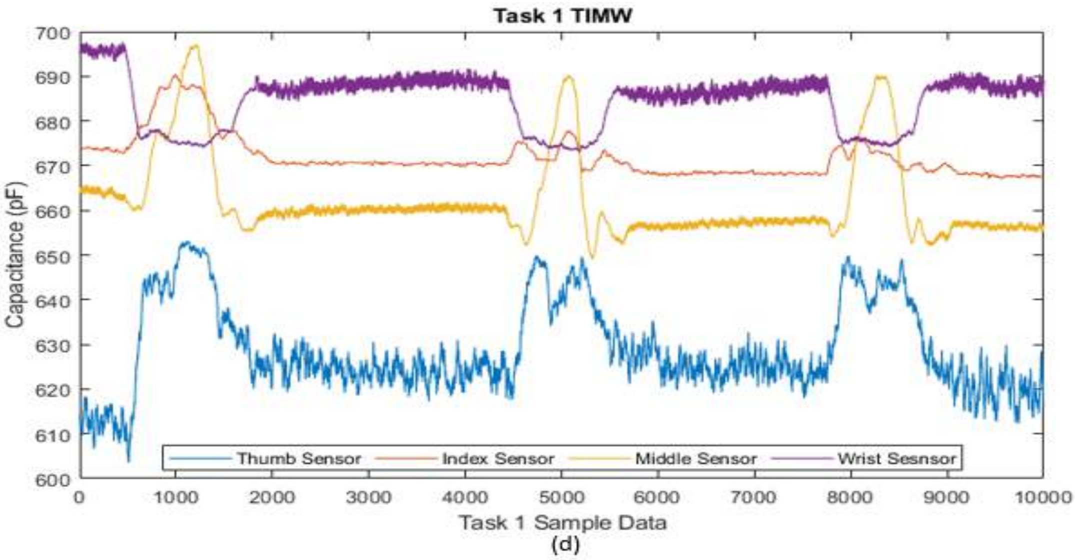
(a)


Task 1 TIWB
Thumb
Index
Wrist
Back of Hand
Capacitance (pF)
Task 1 Sample Data

(b)

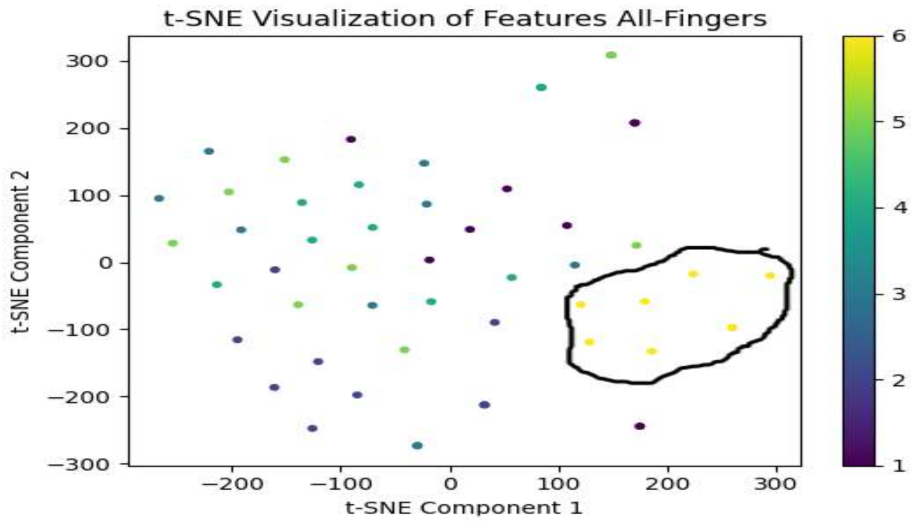

Task 1 TIMB
Thumb
Index
Middle
Back of Hand
Capacitance (pF)
Task 1 Sample Data

(c)

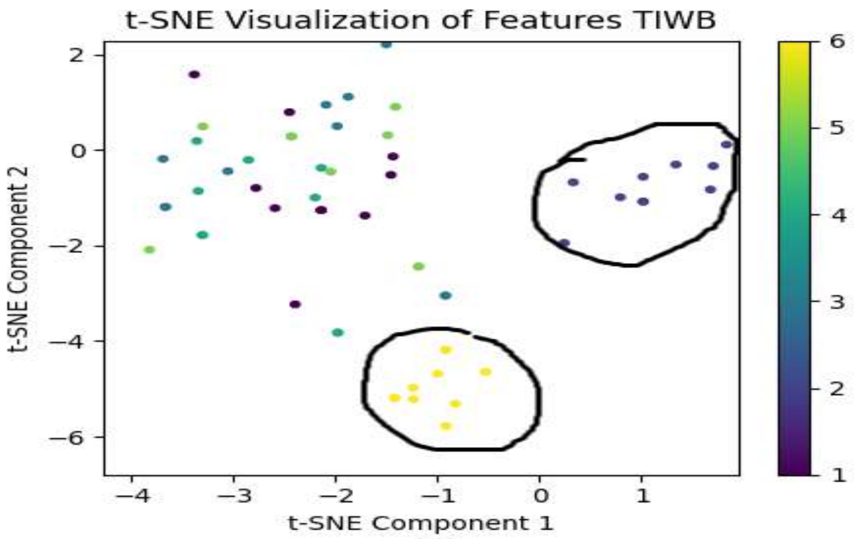


(d)

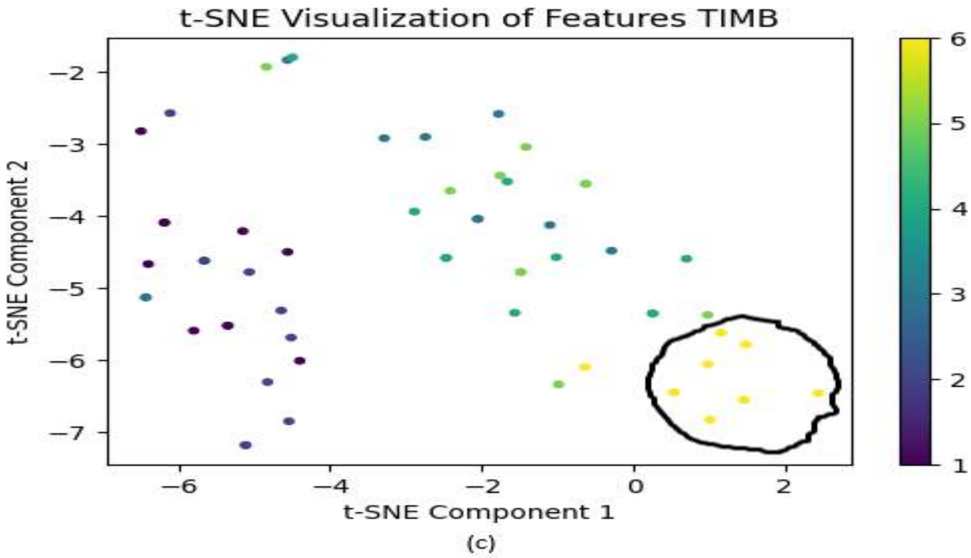
Fig. 6. Raw sensor data for Task 1 with (a) All-Finger (b) TIMB (c) TIWB and (d) TIMW configurations.



(a)



(b)



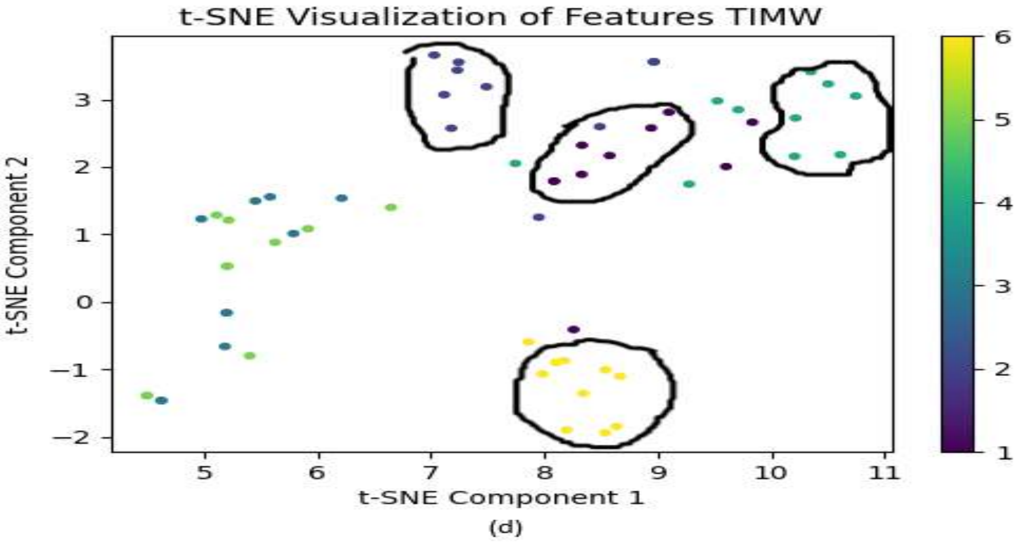


Fig. 7. t-SNE test results for Task 1 with (a) All-fingers (b) TIWB (c) TIMB and (d) TIMW configurations

3.2 Data processing

Outliers resulting from circuit disconnections or partial connections have been eliminated to maintain data quality. Since the dataset contains varying window lengths, multiple smoothing techniques have been applied, including moving average, moving median, moving median absolute deviation, and Gaussian filtering. The most effective technique, which minimized data distortion, has been selected. MATLAB's Data Cleaner app is utilized for both smoothing and outlier removal, with a Gaussian filter applied using a smoothing factor of 0.25. Figures 8 and 9 present the raw dataset and the processed data.

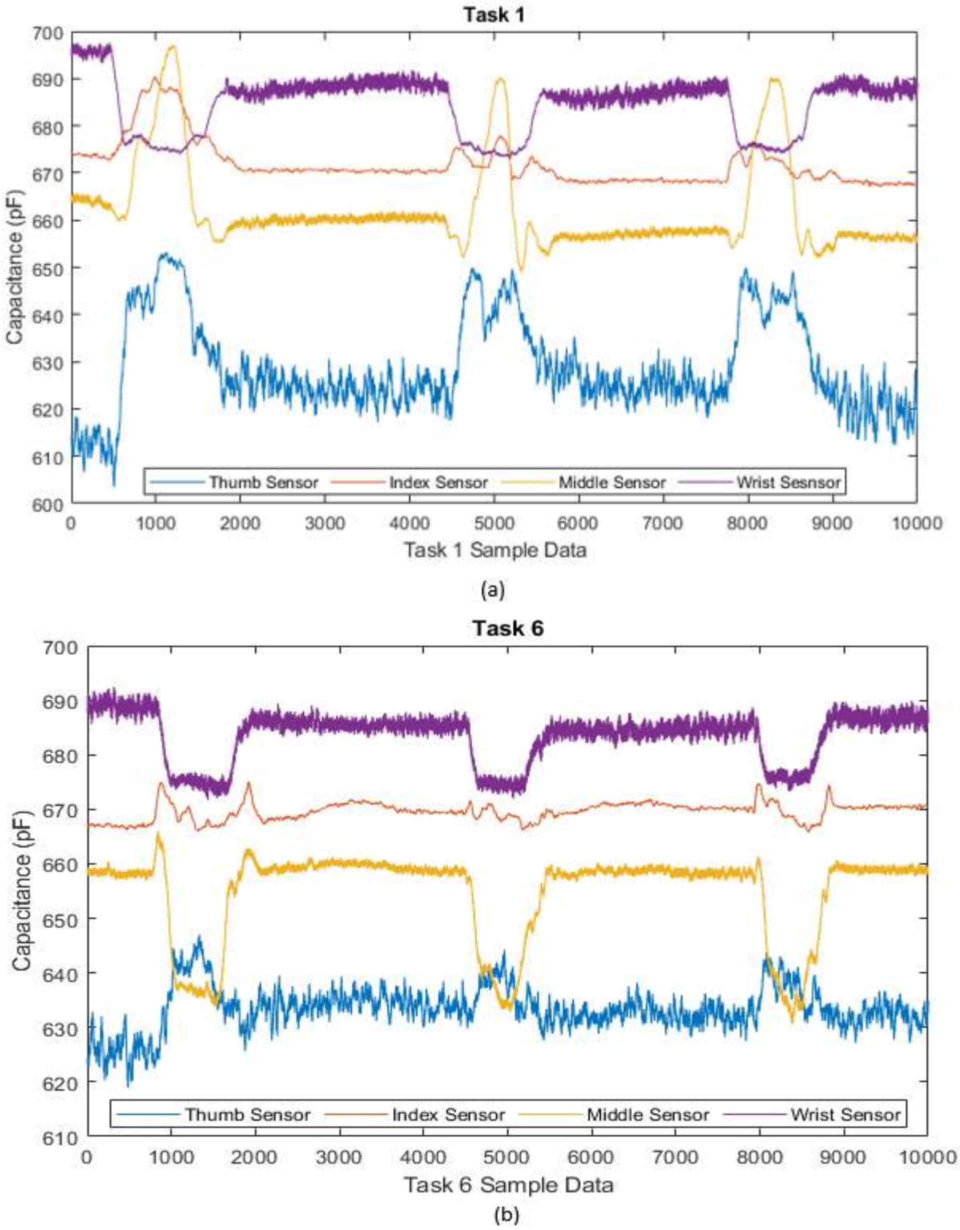
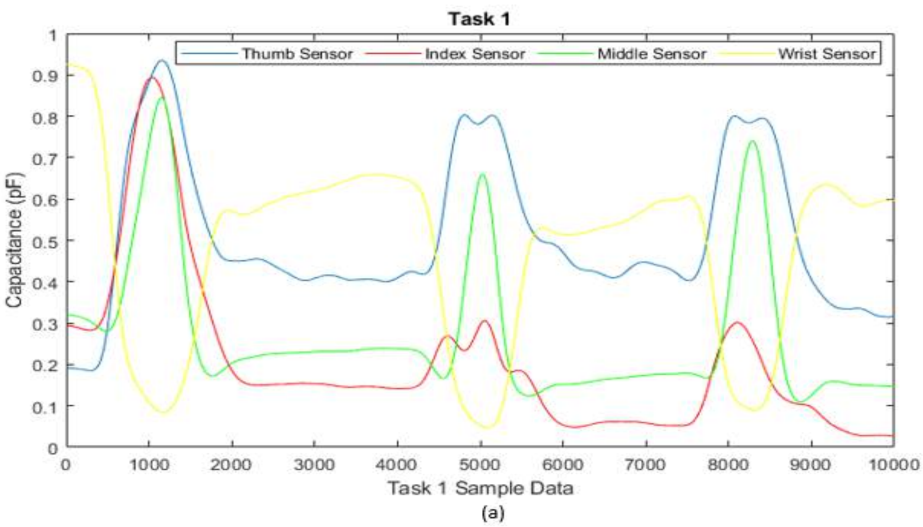


Fig. 8. Raw data for (a) Task 1 (b) Task 2



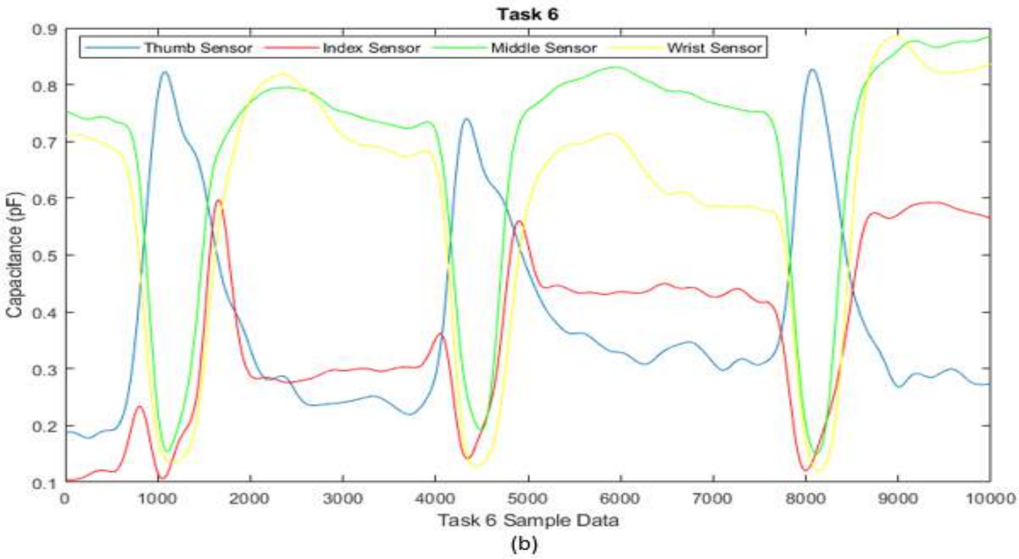


Fig. 9. Processed data for (a) Task 1 (b) Task 6

3.2 Machine learning

The three models have been developed, and the confusion matrix that shows the performance of the model is illustrated as in Figures 10 - 12 for SVM, K-NN and RF algorithms respectively. Tables 4 and 5 outline the performance matrices and the training/testing time for the three algorithms. The hyperparameters, including the number of estimators, number of neighbors, and polynomial degree for the RF, K-NN, and SVM models, have been tuned, and the model selection involve a trade-off between classification accuracy and computational time, as presented in Table 3. The Analysis of Variance (ANOVA) statistical test has been performed on the models' trials to compare their mean accuracies. The results showed an F-statistic of 30.93 and a p-value of 0.0007, indicating that the differences in model accuracy are statistically significant, as the p-value is less than 0.05.

Table 3
Optimized hyperparameters for RF, KNN, SVM models

Model	Metric	n_estimator	Degree	n_neighbour	Training time (s)	Testing time (s)	Accuracy (%)
SVM	Kernel(poly)	-	4	-	9.13	3.10	79.86
RF	Gini	150	-	-	3.66	0.02	38.19
K-NN	Minkowski	-	-	4	0.29	11.66	76.37
SVM	Kernel(poly)	-	3	-	10.20	3.15	86.81
RF	**Gini**	**250**	**-**	**-**	**6.01**	**0.03**	**46.15**
K-NN	**Minkowski**	**-**	**-**	**6**	**0.32**	**11.56**	**95.83**
SVM	**Kernel(poly)**	**-**	**2**	**-**	**11.25**	**3.20**	**97.22**
RF	Gini	300	-	-	7.23	0.04	39.58
K-NN	Minkowski	-	-	7	0.29	11.55	82.54

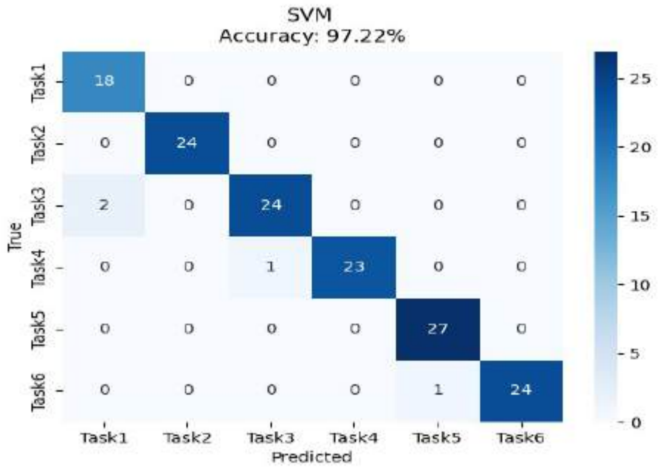


Fig. 10. Confusion matrix for the hand pose recognition using stretchable sensor dataset with SVM algorithm

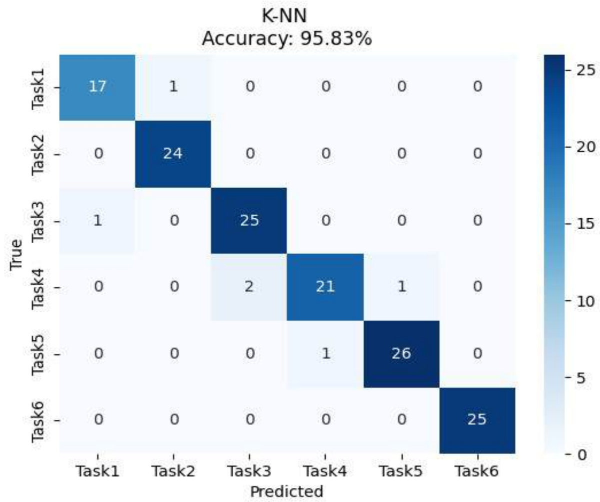


Fig. 11. Confusion matrix for the hand pose recognition using stretchable sensor dataset with K-NN algorithm.

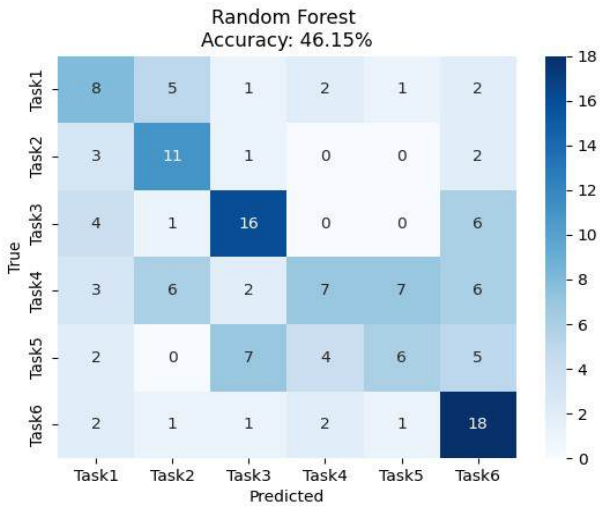


Fig. 12. Confusion matrix for the hand pose recognition using stretchable sensor dataset with RF algorithm

The confusion matrix results Figures 10-12 illustrate an accuracy of 97.22%, 95.83%, and 46.15% for the SVM, and K-NN, and RF ML algorithms respectively. The SVM outcome demonstrates accurate classification for Tasks 1, 2, and 5 as true positives, while tasks 3, 4, and 6 show 2, 1, and 1 false classification respectively as shown in Figure 10. The false classifications are negligible compared to the true positive classification of the testing data. Similarly, Figure 11 illustrated the K-NN algorithm 6 false classification of the tasks which occur at Tasks 1, 3, 4, and 5. However, RF algorithm in Figure 12 presents poor classification with many false classifications of the tasks. This is attributed to the size of the data as RF algorithm accuracy is proportional to data size. Tasks 4 and 5 have been the poorest of all the classification even though a large number have been correctly classified. However, large number have also been incorrectly classified. Tasks 2, 3, and 6 are the best correctly classified task using RF algorithm with 65%, 59%, and 72% 7classification respectively. The result proves that wearable stretchable sensors can be used to recognize the hand pose while performing ADL activities for the 6 ADL task selected. This method also can be applied for patients' assessment in telerehabilitation.

Tables 4 and 5 present the further evaluation of the performance of the developed models using the stretchable sensor dataset for healthy subjects. The performance comparison of SVM, K-NN, and RF shows that SVM achieves the highest accuracy (97.22%), precision (0.97), recall (0.97), and F1-score (0.97), making it the best-performing model. K-NN follows closely with 95.83% accuracy, slightly lower recall, and a comparable F1-score of 0.96. In contrast, RF performs poorly, with only 46.15% accuracy, low precision (0.45), and recall (0.48), indicating frequent misclassifications. Regarding computational time, SVM has the longest training time (11.25 s) but moderate testing time (3.20 sec), while K-NN trains the fastest (0.32 s) but has the longest testing time (11.56 s) due to its instance-based learning. RF balances both, with 6.01 s training time and the fastest testing time (0.03 s). This suggests that while SVM is the most accurate, K-NN is computationally efficient for training, and RF is the fastest for testing but lacks accuracy.

The performance of the three developed machine learning models is summarized in Tables 4 and 5. SVM achieves the highest accuracy, precision, recall, and F1-score but required the longest training and testing time. Table 6 confirms that SVM provides the best classification results for hand pose recognition during ADL tasks using stretchable sensors. K-NN also shows strong performance, particularly with larger datasets.

Previous studies primarily used IMU sensors placed on different body parts for data collection. Halim *et al*. [8] employed three benchmark IMU datasets USC-HAD, IM-WSHA, and MOTIONSENSE

Table 4
Performance Metrics for the Hand Pose Recognition when performing the six ADL tasks classification across ML models

Performance Matric	SVM	K-NN	RF
Accuracy	97.22%	95.83%	46.15%
Precision	0.97	0.96	0.45
Recall	0.97	0.95	0.48
F1-score	0.97	0.96	0.45

Table 5
Training/Testing time for the three ML algorithms

Time (sec)	SVM	K-NN	RF
Training Time	11.25	0.32	6.01
Testing Time	3.20	11.56	0.03

Table 6
Comparison of the number of the previous ML algorithm results with the proposed

Literature	Sensor	ADL(s)	SVM	K-NN	RF	DT	CNN
Halim, N [8]	IMU	6	-	-	0.9316	-	-
Sarka *et al*. [11]	IMU	4 datasets with various ADLs	-	**0.97**	-	-	-
Chen *et al*. [28].	IMU	8	0.97	-	0.79	-	-
Shakerian *et al*. [29]	IMU	7	-	-	-	-	0.90
Shafiqah *et al*. [37]	Flex /Force	3	-	-	-	0.94	-
This study	Stretchable sensor	6	**0.9722**	0.96	0.4615		-

achieving a maximum accuracy of 93.16% using RF as shown in Table 6. However, RF performed poorly on the stretchable sensor dataset, while SVM and K-NN outperformed all IMU-based results. Similarly, Chen et al. [28] used five IMU sensors for 19 ADL/IADL classification, where SVM and RF achieved 97% and 79% accuracy, respectively. The stretchable sensor dataset surpassed these results, achieving 97.22% accuracy with SVM. Shakerian *et al*. [29] developed an IMU-based dataset for real-time ADL recognition using a CNN model, attaining 90.4% accuracy, which was lower than SVM and K-NN on the stretchable sensor dataset in this study. The stretchable sensor's linearity enhances classification accuracy while reducing computational time, making it suitable for real-time applications and telerehabilitation. Its low training and testing time enable real-time hand pose recognition during ADL tasks, supporting patient assessment and rehabilitation monitoring. Comparing the work of Shafiqah *et al.* [37] with this study, the stretchable sensor demonstrates higher accuracy and the ability to recognize twice as many ADL tasks on the manipulation board compared to the flex and force sensor-based approach. Furthermore, the DT algorithm performed well with flex and force sensor but was outperformed by SVM and K-NN when using stretchable sensor. Additionally, stretchable sensor offers greater adaptability, leading to improved classification performance and wider application in rehabilitation and healthcare. Table 7 present the comparison between Shafiqah *et al* [37] and the current study.

Table 7
Comparison of ADL recognition using flex sensor, force sensor and stretchable sensor

Feature	Study with Flex and Force Sensors	Current study with Stretchable sensor
Sensor type	Flex and force	Stretchable
Number of ADL tasks recognize	3	6
Machine learning algorithm used	DT	SVM, K-NN
Best accuracy	94%	97.22% (SVM) and 95.83 (K-NN)
Performance Evaluation	Moderate accuracy with limited number of tasks	High accuracy and recognize more Tasks
Sensor Flexibility	Less flexible, limited to specific tasks	More adaptable to diverse ADL tasks due to higher flexibility

4. Conclusions

In this paper, the performance of hand pose recognition while performing the 6 ADL activities using stretchable sensors has been studied. Recognizing the hand pose while performing ADL tasks remotely is beneficial for delivering rehabilitation exercise remotely. This opens the avenue for enhanced convenience, accessibility, cost-saving and real-time monitoring, and feedback, all of which contribute to improving patient care and satisfaction. Moreover, this method offers an objective assessment, eliminating the subjectivity and inconsistencies that arise from therapists. The wearable stretchable sensor has a linear characteristic which reduces the computational time. Therefore, making it suitable for real time application. SVM algorithm achieves the highest accuracy of 97.22% followed by K-NN algorithm with an accuracy of 95.83% and lastly RF algorithm attains an accuracy of 46.15%. However, for the real time application, a filter needs to be incorporated into the system to reduce the noise effect. At this stage of study, the data of healthy individuals are used to ascertain the baseline data collection and to recognize the hand pose of the individuals while performing the 6 ADL tasks. They also serve as a benchmark for the machine learning classification. Future research will shift towards using data from real patients to recognize their hand poses while conducting the ADLs. Furthermore, in the future work, the recovery level of the patients will be determined based on the stretchable sensor dataset according to the Motor Activity Log (MAL) clinical assessment that is used by the therapists in quantifying the recovery level of the post-stroke patient.

Acknowledgement
The author would like to thank the Asian Office of Aerospace Research and Development (AOARD) for sponsoring the research under Grant Number FA2386-21-1-4026(211OA026).

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